Forecasting Economic Recovery from COVID-19

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Introduction

The COVID-19 pandemic posed an unprecedented global challenge, with significant public health and economic consequences. A central difficulty has been accurately modeling economic recovery under heterogeneous policy responses. Variations in government interventions across countries produced markedly different recovery trajectories, complicating comparative analysis and forecasting. This study investigates whether a generalized yet adaptable framework for forecasting economic resilience can be developed, while accounting for cross-country differences in economic structure and recovery dynamics. Specifically, it examines the relationships between COVID-19 case counts, vaccination rates, policy stringency, as well as pre-pandemic economic performance and each country's economic recovery. By quantifying these associations, the research aims to advance understanding of post-crisis economic dynamics and inform more effective policy responses to future large-scale health shocks.

Literature Review

Current literature on economic recovery from COVID-19 reveals a fragmented approach, where studies often focus on specific indicators or regions. For instance, works such as [7] explore the economic forecasting of advanced and emerging markets but remain limited in scope due to publication timing. Similarly, [11] highlight the challenges of using traditional econometric models to predict recovery following unprecedented events like COVID-19. Studies such as those by [4] discuss the effectiveness of MIDAS models, suggesting potential in nonlinear approaches for capturing economic trends, while [6] and [2] examine the role of fiscal policies in supporting economic resilience. Moreover, [8] and [9] underscore the importance of industry-specific factors, like digital transformation and the differential recovery of small and medium enterprises, which vary widely across regions and sectors.

Our approach seeks to address these gaps by consolidating these fragmented insights into a comprehensive model. Drawing from [3] theory on economic recovery from disasters, our platform will allow users to easily access and interpret economic health data, making it more accessible to non-experts. By integrating current data with models that account for sector-specific nuances, we aim to deliver a tool that helps anticipate future recovery patterns in response to health crises.

Methods

Data

For economic metrics, we sourced data from the World Bank Data Bank, obtaining GDP (in 2015 U.S. dollars), GDP per capita (in 2015 U.S. dollars), and population size for 233 entities from 2019 to 2023[13]. Using these data, we calculated the economic impact of the pandemic for each entity by identifying the lowest GDP observed between 2020 and 2022 ("Minimum Pandemic GDP") and measuring the difference between the Minimum Pandemic GDP and the 2019 GDP. Recovery was quantified by comparing the 2023 GDP to the Minimum Pandemic GDP.

To assess the stringency of public health measures, we utilized the Oxford COVID-19 Government Response Tracker (OxCGRT)[14], which documents 43 different aspects of government responses (e.g., mask mandates, school closures, economic support, vaccine mandates) across 185 entities from January 1, 2020, to December 31, 2022.

The economic and policy datasets were merged using country codes and aggregated at the country level, resulting in a combined dataset covering 162 countries. Among these, 132 countries experienced a Minimum Pandemic GDP below their 2019 GDP. Of these, 112 countries had recovered to either above or below 2019 GDP levels by 2023, while 20 countries had not. Figure 1 (below) illustrates a Sankey diagram illustrating this economic trajectory.

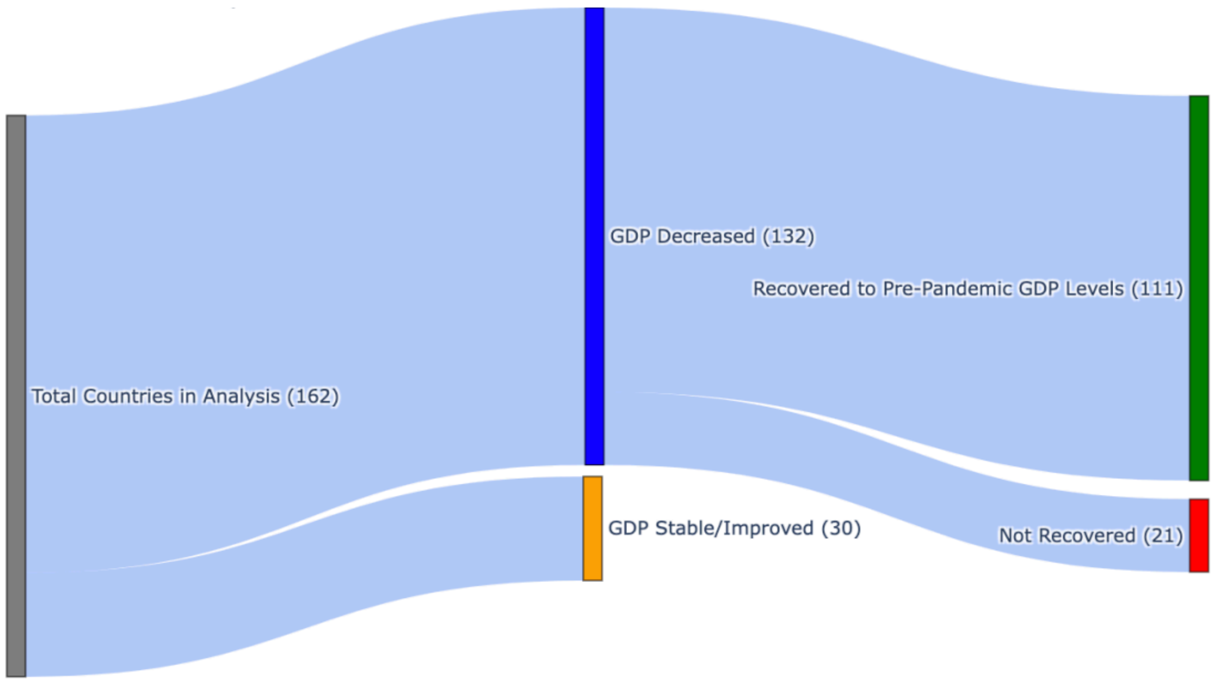


Figure 1. Economic Impact of COVID-19 on Countries

Models Used and Response Variable

To investigate the relationship between public health policies and economic recovery, we employed two machine learning models: linear regression and Random Forest regression. These models were chosen to explore both linear and non-linear associations, providing complementary insights into the factors influencing economic recovery.

The response variable, percent GDP recovery, was calculated as the ratio of recovery GDP (2023 GDP) to the GDP decline during the pandemic (2019 GDP minus Minimum Pandemic GDP). This normalization accounts for disparities between countries with higher and lower GDP, enabling fair comparisons across diverse economic contexts. Predictor variables included public health policy measures, economic metrics from 2019, and population size.

For linear regression models, the strength of relationships was assessed using T-test values, while for Random Forest regression, feature importance scores were used to identify key drivers of economic recovery. Given that these models were utilized primarily for explanatory purposes rather than predictive accuracy, model evaluation focused on statistical significance and goodness of fit rather than performance on a hold-out validation set. This approach ensured a robust interpretation of the underlying relationships between policies and recovery outcomes.

Results

Linear Regression

Initially, the analysis included all countries that experienced a decline in GDP during the pandemic years. However, after examining the model residuals, Lithuania was identified as a significant outlier, skewing the results. To improve the model's reliability, Lithuania was removed, and the regression model was refitted. The results are summarized in Figure 2, which highlights the top 10 predictors ranked by the absolute magnitude of their T-values. These predictors include key public health measures, economic metrics, and policy indicators. Table 1 provides further details about these predictors, including their coefficients, T-values, and p-values.

Table 1. Additional Info about Top 10 Predictors

Predictor	Coef	T Value	P-Value
C3M_Cancel public events	1.54E-02	2.366	0.020
% Decline GDP per Capita	-2.83E+01	-2.362	0.021
C2M_Workplace closing	-1.14E-02	-2.337	0.022
C7M_Flag	-1.63E-02	-2.199	0.031

H1_Public information campaigns	1.87E-02	1.855	0.067
Confirmed Deaths	-3.76E-05	-1.670	0.099
V2D_Medically/ clinically vulnerable (Non-elderly)	-1.68E-02	-1.365	0.176
C2M_Flag	1.16E-02	1.325	0.189
V2A_Vaccine Availability (summary)	9.43E-03	1.315	0.192
C7M_Restrictions on internal movement	5.90E-03	1.167	0.247

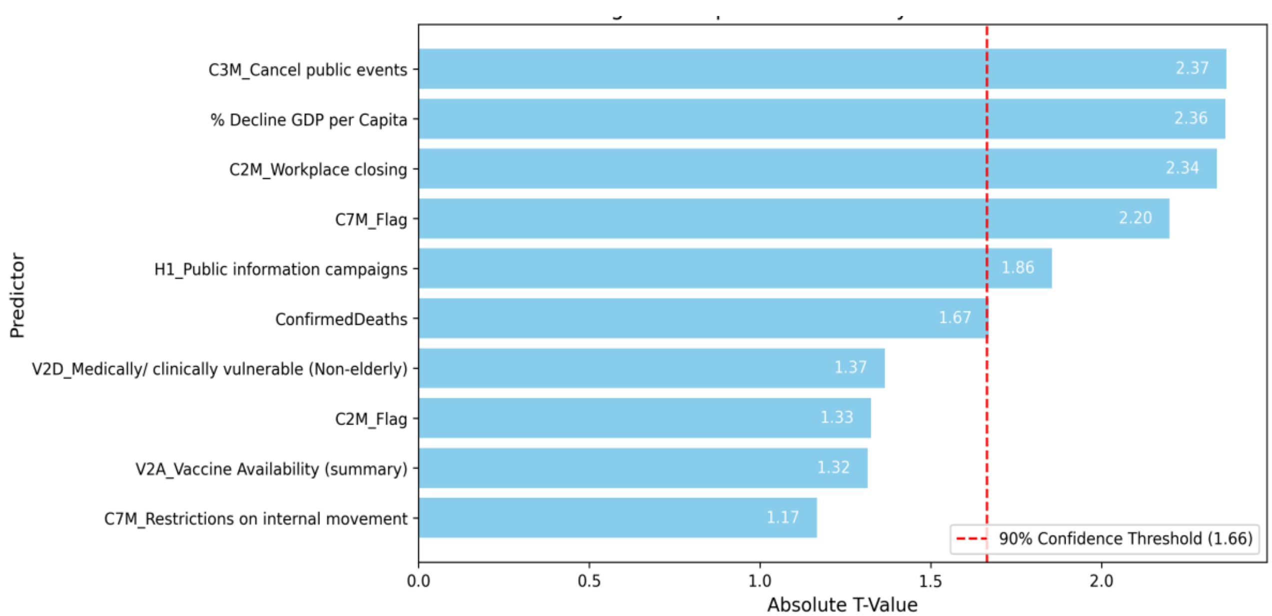
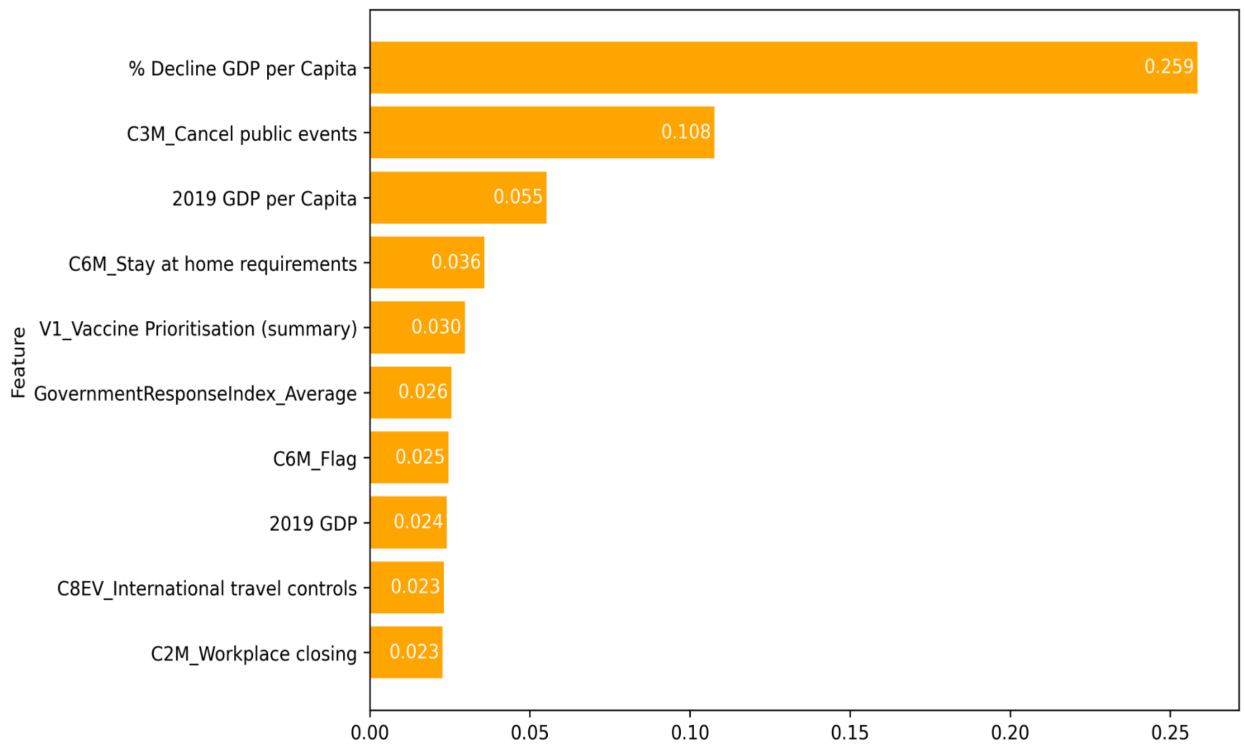


Figure 2. Top 10 Linear Regression Predictors by Absolute Value

Random Forest

Given the relatively small sample size (112 rows) compared to the number of predictors (52 variables), overfitting and bias were significant concerns in our analysis. Random Forest, as an ensemble learning method, has an in-built capability for ranking predictors based on their importance. In addition to its feature selection ability, Random Forest is also a non-parametric model and able to capture more complex, non-linear relationships.

Figure 3 illustrates the top 10 predictors identified by Random Forest based on feature importance. Some of the predictor variables ranked most important are the same as in linear regression (% Decline GDP per Capita, C3M_Cancel public events, C2M_Workplace closing). However, Random Forest also ranks other predictors, such as 2019 GDP per Capita as important, while others, such as ConfirmedDeaths, were not considered so.



Discussion

As seen in the comparison table in Table 2, Random Forest outperforms linear regression in fitting to the data, which makes intuitive sense since the relationship between public policies and economic impact is likely not as straightforward as a simple linear relationship. A major advantage of linear regression, however, when compared with Random Forest is its interpretability—it is much easier to quantify the degree to which predictors affect the economic recovery and in what direction, though feature importances can also be helpful in identifying key decision areas.

Table 2. Summary of Goodness of Fit

Model	R^2	Adjusted R^2
Linear Regression	0.336989	-0.03534
Random Forest Regression	0.883977	0.806628

Conclusion

Our findings demonstrate that incorporating non-linear models, such as Random Forest regression, significantly enhances the ability to predict national economic recoveries from public health crises based on policy decisions. These models outperform traditional linear regression approaches by capturing complex, non-linear relationships that better reflect the multifaceted nature of such scenarios. Quantitatively, the Random Forest model's superior goodness-of-fit measures highlight its effectiveness in identifying key predictors of recovery, such as GDP decline, public event cancellations, and workplace closures.

From a real world-impact perspective, our analysis underscores the limitations of traditional linear models in addressing unprecedented global challenges, such as the COVID-19 pandemic. While our study evaluates a limited set of factors, the results indicate that modern crises demand equally modern modeling approaches. Expanding the range of data sources and predictors would allow for a more comprehensive analysis and provide policymakers with actionable insights to inform strategies for recovery and resilience.

Future Directions

There are several promising avenues for future research:

1. **Segmentation and Clustering**: Countries could be segmented using existing classifications (e.g., geographic areas, OBDC status, socioeconomic status) or through unsupervised clustering algorithms. This would enable the identification of region- or segment-specific recovery patterns and policy impacts.
2. **Binary Recovery Analysis**: Transforming recovery into a binary variable (e.g., recovered vs. not recovered) could provide a new perspective. Logistic regression or classification models could be applied to evaluate the impact of predictors on the likelihood of recovery.
3. **Incorporating Additional Predictors**: Future studies could include a wider range of predictors, such as proximity to the origin of the pandemic, population density, literacy rates, healthcare infrastructure, and digital connectivity. These factors could further enrich the analysis and improve the explanatory power of the models.

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